Hyperspectral Remote Sensing of Vegetation: Knowledge Gain and Knowledge Gap After 40 years of Research

Prasad S. Thenkabail
Research Geographer, U.S. Geological Survey (USGS)
Landsat Science Team Meeting
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“More Data (e.g., spectral, spatial, temporal, radiometric) is good. Better understanding of data for application of interest is better. However, current knowledge gap in understanding data and it’s uncertainty is far greater than we want to admit.”
- A Thought for the lecture.

- P. forest
- Slash&Burn
- Raphia palm
- Bamboo
- P. Africana

- HY910
- HY675
- HY10
- HY675
- Reflectance (percent)
- Wavelength (nm)
- barley
- wheat

“More Data (e.g., spectral, spatial, temporal, radiometric) is good. Better understanding of data for application of interest is better. However, current knowledge gap in understanding data and it’s uncertainty is far greater than we want to admit.”
- A Thought for the lecture.
Importance of Hyperspectral Sensors (Imaging Spectrometry) in Study of Vegetation
Hyperspectral Remote Sensing of Vegetation
Importance of Hyperspectral Sensors (Imaging Spectroscopy) in Study of Vegetation

More specifically……………..hyperspectral Remote Sensing, originally used for detecting and mapping minerals, is increasingly needed for to characterize, model, classify, and map agricultural crops and natural vegetation, specifically in study of:

(a) Species composition (e.g., *chromolenea odorata* vs. *imperata cylindrica*);
(b) Vegetation or crop type (e.g., soybeans vs. corn);
(c) Biophysical properties (e.g., LAI, biomass, yield, density);
(d) Biochemical properties (e.g, Anthrocyanins, Carotenoids, Chlorophyll);
(e) Disease and stress (e.g., insect infestation, drought),
(f) Nutrients (e.g., Nitrogen),
(g) Moisture (e.g., leaf moisture),
(h) Light use efficiency,
(i) Net primary productivity and so on.

……………in order to increase accuracies and reduce uncertainties in these parameters………

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U.S. Geological Survey
U.S. Department of Interior
Reflectance spectra of leaves from a senesced birch (Betula), ornamental beech (Fagus) and healthy and fully senesced maple (AcerLf, AcerLlt) illustrating Carotenoid (Car), Anthocyanin (Anth), Chlorophyll (Chl), Water and Ligno-cellulose absorptions.

The reflectance spectra with characteristic absorption features associated with plant biochemical constituents for live and dry grass (Adapted from Hill [13]).
Definition of Hyperspectral Sensors (Imaging Spectrometry) in Study of Vegetation
Hyperspectral Remote Sensing of Vegetation

Definition of Hyperspectral Data

A. consists of hundreds or thousands of narrow-wavebands (as narrow as 1; but generally less than 5 nm) along the electromagnetic spectrum;

B. it is important to have narrowbands that are contiguous for strict definition of hyperspectral data; and not so much the number of bands alone (Qi et al. in Chapter 3, Goetz and Shippert).

............Hyperspectral Data is fast emerging to provide practical solutions in characterizing, quantifying, modeling, and mapping natural vegetation and agricultural crops.
The advantage of airborne, ground-based, and truck-mounted sensors are that they enable relatively cloud free acquisitions that can be acquired on demand anywhere; over the years they have also allowed careful study of spectra in controlled environments to advance the genre.
Hyperspectral Remote Sensing of Vegetation

Spaceborne Hyperspectral Imaging Sensors: Some Characteristics

There are some twenty spaceborne hyperspectral sensors

The advantages of spaceborne systems are their capability to acquire data: (a) continuously, (b) consistently, and (c) over the entire globe. A number of system design challenges of hyperspectral data are discussed in Chapter 3 by Qi et al. Challenges include cloud cover and large data volumes.

The 4 near future hyperspectral spaceborne missions:
1. PRISMA (Italy’s ASI’s),
2. EnMAP (Germany’s DLR’s), and
3. HISUI (Japanese JAXA);
4. HyspIRI (USA’s NASA).

will all provide 30 m spatial resolution hyperspectral images with a 30 km swath width, which may enable a provision of high temporal resolution, multi-angular hyperspectral observations over the same targets for the hyperspectral BRDF characterization of surface.

The multi-angular hyperspectral observation capability may be one of next important steps in the field of hyperspectral remote sensing.

Existing hyperspectral spaceborne missions:
1. Hyperion (USA’s NASA),
2. PROBA (Europe’s ESA’s), and
Hyperspectral Remote Sensing of Vegetation
Earth and Planetary Hyperspectral Remote Sensing Instruments

<table>
<thead>
<tr>
<th>Hyperspectral Instrument</th>
<th>Spectral Range (nm)</th>
<th># of Channels</th>
<th>Spectral Bandwidth</th>
<th>Spatial Resolution</th>
<th>Operational Dates</th>
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<tbody>
<tr>
<td>Earth</td>
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<tr>
<td>AVIRIS</td>
<td>380 - 2500</td>
<td>224</td>
<td>10 nm</td>
<td>4 - 20 m</td>
<td>1999 - present</td>
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<tr>
<td>ProSpecTIR-VR2</td>
<td>400 - 2450</td>
<td>256</td>
<td>2.3 - 20 nm</td>
<td>1 - 10 m</td>
<td>~2000 - present</td>
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<tr>
<td>HyMap</td>
<td>400 - 2500</td>
<td>128</td>
<td>15 nm</td>
<td>2 - 10 m</td>
<td>~1997 - present</td>
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<td>CASI</td>
<td>400 - 1000</td>
<td>288</td>
<td>2 - 12 nm</td>
<td>0.5 - 10 m</td>
<td>~1990 - present</td>
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<tr>
<td>SFG</td>
<td>1230 - 2380</td>
<td>230</td>
<td>10 nm</td>
<td>0.5 - 10 m</td>
<td>1990 - present</td>
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<td>Spaceborne</td>
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<tr>
<td>EO-1 Hyperion</td>
<td>400 - 2500</td>
<td>220</td>
<td>10 nm</td>
<td>30 m</td>
<td>2001 - present</td>
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<td>Mercury</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>MESSENGER MASCs7</td>
<td>220 - 1450</td>
<td>768</td>
<td>0.2 - 0.5 nm</td>
<td>1 - 650 km</td>
<td>2004 - present</td>
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<tr>
<td>Moon</td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>Chandrayaan-1 Moon Mineralogy Mapper</td>
<td>400 - 2900</td>
<td>260</td>
<td>10 nm</td>
<td>70 - 140 m</td>
<td>2008 - 2009</td>
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<tr>
<td>Mars</td>
<td></td>
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<tr>
<td>Mars Express OMEGA</td>
<td>350 - 5100</td>
<td>352</td>
<td>7 - 20 nm</td>
<td>300 m - 4.8 km</td>
<td>2003 - present</td>
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<tr>
<td>Mars Reconnaissance Orbiter CRISM</td>
<td>362 - 3920</td>
<td>545</td>
<td>6.55 nm</td>
<td>15.7 m - 200 m</td>
<td>2005 - present</td>
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<tr>
<td>Jupiter</td>
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<tr>
<td>Galileo NIMS9</td>
<td>700 - 5200</td>
<td>1 - 408</td>
<td>12.5 &amp; 25 nm</td>
<td>50 - 500 km</td>
<td>1999 - 2003</td>
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<tr>
<td>Saturn</td>
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<td></td>
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<tr>
<td>Cassini VIMS11</td>
<td>300 - 5100</td>
<td>352</td>
<td>7 &amp; 14 nm</td>
<td>10 - 20 km</td>
<td>1997 - present</td>
</tr>
</tbody>
</table>

1. Airborne Visible Infrared Imaging Spectrometer (http://aviris.jpl.nasa.gov/)
4. Compact Airborne Spectrographic Imager (http://www.geomatics-group.co.uk/GeoCMS/Products/CASL.aspx)
5. SWIR Full Spectrum Imager (http://www.boston.com/tsi.html)
7. Mercury Atmospheric and Surface Composition Spectrometer (http://www.messenger-education.org/instruments/mascos.htm)
8. M3 (http://moonmineralogymapper.jpl.nasa.gov/INSTRUMENT/)
10. Compact Reconnaissance Imaging Spectrometer for Mars (http://crism.jhuapl.edu/)

See chapter 27, Vaughan et al.
## Comparison of Hyperspectral Data with Data from Other Advanced Sensors

Hyperspectral, Hyperspatial, and Advanced Multi-spectral Data

<table>
<thead>
<tr>
<th>Satellite/Sensor or pixels</th>
<th>spatial resolution (meters)</th>
<th>spectral bands (#)</th>
<th>data points per hectare</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Earth Observing-1</strong></td>
<td></td>
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<tr>
<td>Hyperion</td>
<td>30</td>
<td>196 (400-2500 nm)</td>
<td>11.1</td>
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<tr>
<td>ALI</td>
<td>10 m (P), 30 m (M)</td>
<td>1, 9</td>
<td>100, 11.1</td>
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<tr>
<td><strong>IKONOS 2</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Spacel Imaging</td>
<td>1 m (P), 4 m (M)</td>
<td>4</td>
<td>10000, 625</td>
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<td><strong>QUICKBIRD</strong></td>
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<tr>
<td>Digital Globe</td>
<td>0.61 m (P), 2.44 m (M)</td>
<td>4</td>
<td>16393, 4098</td>
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<td><strong>Terra: Earth Observing System (EOS)</strong></td>
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<tr>
<td>ASTER</td>
<td>15 m, 30 m, 90 m (VNIR,SWIR,TIR)</td>
<td>4,6,5</td>
<td>44.4,11.1,11.26</td>
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<tr>
<td>MODIS</td>
<td>250-1000 m</td>
<td>36</td>
<td>0.16, 0.01</td>
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<tr>
<td>Landsat-7 ETM+</td>
<td>15 m (P), 30 m (M)</td>
<td>7</td>
<td>44.4,11.1</td>
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<tr>
<td>Landsat-4, 5 TM</td>
<td>30 m (M)</td>
<td>7</td>
<td>11.1</td>
</tr>
<tr>
<td><strong>SPOT-1,2,3, 4,5 HRV</strong></td>
<td>2.5 m, 5m, 10 m (P/M), 20 m (M)</td>
<td>4</td>
<td></td>
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<tr>
<td><strong>IRS-1C LISS</strong></td>
<td>5 m (P), 23.5 m (M)</td>
<td>3</td>
<td>400, 18.1</td>
</tr>
<tr>
<td><strong>IRS-1D LISS</strong></td>
<td>5 m (P), 23.5 m (M)</td>
<td>3</td>
<td>400, 18.1</td>
</tr>
</tbody>
</table>
Hyperion Data from EO-1 (e.g., in Rainforests of Cameroon)

Hyperspectral Data Cube Providing Near-continuous data of 100’s of Wavebands

3-D cube of Hyperion data for Cameroon rainforests: 196 bands

Top-layer: FCC(RGB): 890 nm, 680 nm, and 550 nm

Region 1

Region 2

Reflectance (%)
Hyperion Narrow-Band Data from EO-1 Vs. ETM+ Broad-band Data

Hyperspectral Data Provides Numerous Ways of Looking at Data

ETM+: 4, 3, 2

Hyperion: 843, 680, 547

Hyperion: 680, 547, 486

Hyperion: 905, 680, 547

Hyperion: 905, 962, 680

Hyperion: 1245, 680, 547

Hyperion: 1642, 905, 680

Hyperion: 904, 680, 1245
Comparison of Hyperspectral Data with Data from Other Advanced Sensors

Hyperspectral, Hyperspatial, and Advanced Multi-spectral Data

IKONOS: Feb. 5, 2002 (hyper-spatial)

ETM+: March 18, 2001 (multi-spectral)

ALI: Feb. 5, 2002 (multi-spectral)

Hyperion: March 21, 2002 (hyper-spectral)
Hyperspectral Data Characteristics
Spectral Wavelengths and their Importance in Vegetation Studies
Fraction images of a pasture property in the Amazon derived from EO-1 Hyperion imagery. **Four endmembers:** (a) nonphotosynthetic vegetation (NPV); (b) green vegetation (GV); (c) Soil; and (d) Shade.

See chapter 9, Numata et al.
Hyperspectral Data on Tropical Forests
Factors Influencing Spectral Variation over Tropical Forests

1. Biochemistry (e.g., plant pigments, water, and structural carbohydrates):
   Leaf reflectance in the visible spectrum is dominated by absorption features created by plant pigments, such as:
   - **chlorophyll a (chl-a):** absorbs in 410-430 nm and 600-690 nm;
   - **chlorophyll b (chl-b):** absorbs in 450-470 nm;
   - **carotenoids (e.g., β-carotene and lutein):** peak absorption in wavebands <500 nm; and
   - **anthocyanins.**
   **Lignin, cellulose, protein, Nitrogen:** relatively low reflectance and strong absorption in **SWIR bands** by water that masks other absorption features.

..............However, dry leaves do not have strong water absorption and reveal overlapping absorptions by carbon compounds, such as lignin and cellulose, and other plant biochemicals, including protein nitrogen, starch, and sugars.

Note: see chapter 18, Clark et al.
Hyperspectral Data on Tropical Forests
Factors Influencing Spectral Variation over Tropical Forests

2. Structure or biophysical (e.g., leaf thickness and air spaces): of leaves, and the scaling of these spectral properties due to volumetric scattering of photons in the canopy;

3. Nonphotosynthetic tissues (e.g., bark, flowers, and seeds); and

4. Other photosynthetic canopy organisms (e.g., vines, epiphytes, and epiphylls) can mix in the photon signal and vary depending on a complex interplay of species, structure, phenology, and site differences,

.................................................currently, none of which are well understood.

Note: see chapter 18, Clark et al.
Hyperspectral Data on Tropical Forests
Individual Tree Crown Delineation: Illustrated for 2 species

"Fractional abundance of green vegetation (green), non-photosynthetic vegetation (red) and photometric shade (blue) from a spectral mixture analysis.

Individual tree crowns delineated with visual interpretation: *Dipteryx panamensis* (DIPA) and *Hyeronima alchorneoides* (HYAL)."

Note: see chapter 18, Clark et al.
Hyperspectral Data on Vegetation from
A Forest-Margin Benchmark Area

African savannas and Rainforests:
Wide range of vegetation including forest and savanna
vegetation and agricultural crops studies using
Hyperion and Spectroradiometer data.
Hyperspectral Data of Two Dominant Weeds

Chromolaena Odorata in African Rainforests vs. Imperata Cylindrica in African Savannas

Mean reflectance of Chromolaena odorata and Imperata cylindrica
Nigeria-Benin 2000

- Chromolaena odorata (n=67)
- Imperata cylindrica (n=45)

Reflectance factor

Wavelength (nanometer)

Chromolaena Odorata

Imperata Cylindrica
Hyperspectral Data Gathered for the Following Rainforest Vegetation using Hyperion EO-1 Data and Field-based Measurements of Biophysical Characteristics

- Primary forests
- Degraded primary forests
- Secondary forests
- Musanga regrowth
- Raphia palm lowland
- Permanently flooded swamp forest
- Degraded permanently flooded swamp forest
- Forest fragmentation along roads
- Slash-and-burn
- Slash-and-burn agriculture
- 2-yr regrowth Chromolaena Odorata
- 50-yr regrowth
- Cocoa plantations
Hyperspectral Remote Sensing of Vegetation
Mega file Data Cube (MFDC) of Hyperion Sensor onboard EO-1

e.g. MFDC of African Rainforests in Cameroon

Hyperion: VNIR reflectance
(Mean spectral plots of landuse/landcover types)

Hyperion has 220 bands in 400-2500 nm

Note: Currently NASA is planning a next Spaceborne Hyperspectral mission called: HyspIRI

FCC (RGB): 680, 547, 486

FCC (RGB): 1245, 680, 547

Note: Currently NASA is planning a next Spaceborne Hyperspectral mission called: HyspIRI

USGS science for a changing world
U.S. Geological Survey
U.S. Department of Interior
Hyperspectral Data Gathered for the Following Rainforest Vegetation using Hyperion EO-1 Data
Hyperspectral Data Gathered for the Following Rainforest Vegetation using Hyperion EO-1 Data

- Y. sec. Forest
- P. forest
- Slash&Burn
- Raphia palm
- Bamboo
- P. Africana

Hyperion FCC(RGB): 890 nm, 680 nm, and 550 nm
Hyperspectral Data of Vegetation Species and Agricultural Crops

Illustrations for Numerous Vegetation Species from African Savannas

a. Crop species

b. Shrub species

c. Grass species

d. Weed species
Hyperspectral Data on Vegetation from A Desert-Margin Benchmark Area

Desert-margin: Agricultural cropland vegetation characteristics studied using Hand-held Spectroradiometer Hyperspectral Data

Forest-margin: Rainforest vegetation characteristics studied using Hyperion Spaceborne Hyperspectral Data

About 50 km by 50 km (part of Landsat-5 TM Path: 174, Row: 35)
Wheat Crop Versus Barley Crop Versus Fallow Farm
Hyperspectral narrow-band Data for an Erectophile (65 degrees) canopy Structure

- Wheat (64)
- Barley (44)
- Fallow (9)

- Peak NIR reflectance around 910 nanometers.
- Erectophile (65 degrees) structure results in steep slopes in NIR reflectance from 740-nm to 940-nm.
- Moisture sensitive and biomass related trough centered around 980 nanometers.
- Higher reflectance of barley throughout visible spectrum as a result of pigmentation. Barley greenish brown/seafoam color compared to deep green of wheat.
- Absorption maxima around 680 nanometers.
Hyperspectral Remote Sensing of Vegetation
Spectral Wavelengths and their Importance in the Study of Vegetation Structure

![Graph showing reflectance versus wavelength for different vegetation types.](image)

- **Erectophile (e.g., wheat)**
- **Planophile (e.g., soybeans)**

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Hyperspectral Remote Sensing of Vegetation
Spectral Wavelengths and their Importance in the Study of Vegetation over Time

Typical reflectance spectra in agro-ecosystem surfaces (upper), and seasonal changes of spectra in a paddy rice field (lower).
Hyperspectral Remote Sensing of Vegetation
Spectral Wavelengths and their Importance in the Study of Vegetation Stress

See chapter 23
Hyperspectral Remote Sensing of Vegetation
Spectral Wavelengths and their Importance in the Study of Vegetation in different Growth Stages

(a) Cotton (critical)
(b) Soybeans (early)
(c) Potato (early)

(a) Cotton (flowering/senescing)
(b) Soybeans (critical)
(c) Potato (mid-vegetative)

Data was Gathered at Various Growth Stages
Hyperspectral Remote Sensing of Vegetation
Spectral Wavelengths and their Importance in the Study of Vegetation in different Growth Stages

- **wheat**
  - Yielding (50)
  - Critical (23)
  - Soil (43)

- **potato**
  - Early vege (17)
  - Late vege (8)

- **soybeans**
  - Early vege (13)
  - Critical (14)

- **Cotton**
  - Late vege (6)
  - Critical (11)

Reflectance (%) at different wavelengths for various vegetation stages.
Hughes Phenomenon
(or Curse of High Dimensionality of Data) and
overcoming data redundancy through Data Mining
Hyperspectral Data (Imaging Spectroscopy data)

Not a Panacea!

For example, hyperspectral systems collect large volumes of data in a short time. Issues include:

- data storage volume;
- data storage rate;
- downlink or transmission bandwidth;
- computing bottle neck in data analysis; and
- new algorithms for data utilization (e.g., atmospheric correction more complicated).
Data Mining Methods and Approaches in Vegetation Studies
Lambda by Lambda R-square Contour Plots: Identifying Least Redundant Bands

Hyperion rainforest vegetation: Least redundant bands

Highly redundant: bands centered at 680 nm and 690 nm

Significantly different: bands centered at 680 nm and 890 nm

Lambda vs. Lambda Correlation plot for African rainforest Vegetation

R² values between wavebands (lesser the R² value lesser the redundancy)

- 0.009-0.01
- 0.008-0.009
- 0.007-0.008
- 0.006-0.007
- 0.005-0.006
- 0.004-0.005
- 0.003-0.004
- 0.002-0.003
- 0.001-0.002
- 0.001

Distinctly different: bands centered at 920 nm and 2050 nm
Feature selection is necessary in any data mining effort. Feature selection reduces the dimensionality of data by selecting only a subset of measured features (predictor variables). Feature selection methods recommendation based on:

(a) Information Content (e.g., Selection based on Theoretical Knowledge, Band Variance, Information Entropy),
(b) Projection-Based methods (e.g., Principal Component Analysis or PCA, Independent Component Analysis or ICA),
(c) Divergence Measures (e.g., Distance-based measures),
(d) Similarity Measures (e.g.,Correlation coefficient, Spectral Derivative Analysis), and
(e) Other Methods (e.g., wavelet Decomposition Method).

Note: see chapter 4
### Data Mining Methods and Approaches in Vegetation Studies

#### Principal Component Analysis: Identifying Most useful Bands

**Wavebands with Highest Factor Loadings**

<table>
<thead>
<tr>
<th>Crops</th>
<th>PCA1</th>
<th>PCA2</th>
<th>PCA3</th>
<th>PCA4</th>
<th>PCA5</th>
<th>% variability explained</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cassava</td>
<td>1725;1715;1705;1695;1695;1675;</td>
<td>635;625;695;615;645;695;595;6</td>
<td>2002;2342;2322;2272;2145;2132</td>
<td>2002;1245;1255;1235;1275;1</td>
<td>2332;2342;2322;1982;2312;2312;1445;2242;2262;2062;2292;2222;2222;2262;1982;2272;2232;2145;2132</td>
<td>63.9</td>
</tr>
<tr>
<td>Dominating</td>
<td>1555;1595;1565;1685;1625;1655;</td>
<td>515;585;555;545;715;565;535;5</td>
<td>2002;2342;2322;2272;2145;2132</td>
<td>2002;1245;1255;1235;1275;1</td>
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<td>63.9</td>
</tr>
<tr>
<td>Corn</td>
<td>1675;1665;1645;1655;1685;1695;</td>
<td>2032;2052;2042;2082;2072;2062;</td>
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</table>

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U.S. Department of Interior*
Methods of Modeling Vegetation Characteristics using Hyperspectral Vegetation Indices (HVI's)
Hyperspectral Data (Imaging Spectroscopy data)

Hyperspectral Vegetation Indices (HVIs)

Unique Features and Strengths of HVIs

1. Eliminates redundant bands
   - removes highly correlated bands

2. Physically meaningful HVIs
   - e.g., Photochemical reflective index (PRI) as proxy for light use efficiency (LUE)

3. Significant improvement over broadband indices
   - e.g., reducing saturation of broadbands, providing greater sensitivity (e.g., an index involving NIR reflective maxima @ 900 nm and red absorption maxima @ 680 nm)

4. New indices not sampled by broadbands
   - e.g., water-based indices (e.g., involving 970 nm or 1240 nm along with a nonabsorption band)

5. Multi-linear indices
   - indices involving more than 2 bands
Methods of Modeling Vegetation Characteristics using Hyperspectral Indices

Hyperspectral Two-band Vegetation Indices (TBVIs) = 12246 unique indices for 157 useful Hyperion bands of data

$$HTBVI_{ij} = \frac{(R_j - R_i)}{(R_j + R_i)}$$

- **Hyperion:**
  - A. acquired over 400-2500 nm in 220 narrow-bands each of 10-nm wide bands. Of these there are 196 bands that are calibrated. These are: (i) bands 8 (427.55 nm) to 57 (925.85 nm) in the visible and near-infrared; and (ii) bands 79 (932.72 nm) to band 224 (2395.53 nm) in the short wave infrared.
  - B. However, there was significant noise in the data over the 1206–1437 nm, 1790–1992 nm, and 2365–2396 nm spectral ranges. When the Hyperion bands in this region were dropped, 157 useful bands remained.

- **Spectroradiometer:**
  - A. acquired over 400-2500 nm in 2100 narrow-bands each of 1-nm wide. However, 1-nm wide data were aggregated to 10-nm wide to coincide with Hyperion bands.
  - B. However, there was significant noise in the data over the 1350-1440 nm, 1790-1990 nm, and 2360-2500 nm spectral ranges. This was seriously affected by atmospheric absorption and noise. The remaining good noise free data were in 400-1350 nm, and 1440-1790 nm, 1990-2360 nm.

- So, for both Hyperion and Spectroradiometer we had 157 useful bands, each of 10-nm wide, over the same spectral range.

- where, $i, j = 1, N$, with $N=$number of narrow-bands$= 157$ (each band of 1 nm-wide spread over 400 nm to 2500 nm), $R=$reflectance of narrow-bands.

**Model algorithm:** two band NDVI algorithm in Statistical Analysis System (SAS). Computations are performed for all possible combinations of $\lambda_1$ (wavelength 1 = 157 bands) and $\lambda_2$ (wavelength 2 = 157 bands), a total of 24,649 possible indices. It will suffice to calculate Narrow-waveband NDVI’s on one side (either above or below) the diagonal of the 157 by 157 matrix as values on either side of the diagonal are the transpose of one another.
Methods of Modeling Vegetation Characteristics using Hyperspectral Indices
Lambda vs. Lambda R-square contour plot on non-linear biophysical quantity (e.g., biomass) vs. HTBVI models

Illustrated for 2 crops here
Methods of Modeling Vegetation Characteristics using Hyperspectral Indices

Non-linear biophysical quantities (e.g., biomass, LAI) vs.: (a) Broadband models (top two), & (b) Narrowband HTBVI models (bottom two)

**broad-band NDVI43 vs. LAI**

- LAI = 0.2465e^{3.2919*NDVI43}
- \( R^2 = 0.5868 \)

**broad-band NDVI43 vs. WBM**

- WBM = 0.186e^{3.6899*NDVI43}
- \( R^2 = 0.6039 \)

**narrow-band NDVI43 vs. LAI**

- LAI = 0.1178e^{3.8073*NDVI910675}
- \( R^2 = 0.7129 \)

**narrow-band NDVI43 vs. WBM**

- WBM = 0.1106e^{3.9254*NDVI910675}
- \( R^2 = 0.7398 \)

HTBVI models explain about 13 percent Greater Variability than Broad-band TM indices in modeling LAI and biomass.
Developing Allometric Equations
in African Rainforests

\[ y = 0.0763x^{2.566} \]  
\[ R^2 = 0.92 \]  
(eq. 4)
Methods of Modeling Vegetation Characteristics using Hyperspectral Indices

Lambda vs. Lambda R-square contour plot on non-linear biophysical quantity (e.g., biomass) vs. HTBVI models

Waveband combinations with greatest $R^2$ values
Greater are ranked…….bandwidths can also be determined.
Rainforest Vegetation Studies: biomass, tree height, land cover, species in African Rainforests

- Fallows biomass
- dbh
- Tree height
- LULC
- Road network and logging
- Digital photographs
Methods of Modeling Vegetation Characteristics using Hyperspectral Indices

Hyperspectral Multi-band Vegetation Indices (HMBVIs)

\[
\text{HMBVI}_i = \sum_{j=1}^{N} a_{ij} R_j
\]

where, OMBVI = crop variable \( i \), \( R \) = reflectance in bands \( j \) (\( j = 1 \) to \( N \) with \( N = 157 \); \( N \) is number of narrow wavebands); \( a \) = the coefficient for reflectance in band \( j \) for \( i \) th variable.

**Model algorithm**: MAXR procedure of SAS (SAS, 1997) is used in this study. The MAXR method begins by finding the variable \( (R_j) \) producing the highest coefficient of determination \( (R^2) \) value. Then another variable, the one that yields the greatest increase in \( R^2 \) value, is added...............and so on......so we will get the best 1-variable model, best 2-variable model, and so on to best \( n \)-variable model...............when there is no significant increase in \( R^2 \)-value when an additional variable is added, the model can stop.
Methods of Modeling Vegetation Characteristics using Hyperspectral Indices

Predicted biomass derived using MBVI’s involving various narrowbands in African Rainforests

Note: Increase in $R^2$ values beyond 6 bands is negligible

Note: Increase in $R^2$ values beyond 11 bands is negligible

Note: Increase in $R^2$ values beyond 17 bands is negligible

- Fallow (n=10)
- Primary forest (n=16)
- Secondary forest (n=26)
- Primary forest + secondary forest + fallow (n=52)
Methods of Modeling Vegetation Characteristics using Hyperspectral Indices

Hyperspectral Derivative Greenness Vegetation Indices (DGVIs)

**First Order Hyperspectral Derivative Greenness Vegetation Index (HDGVI)** (Elvidge and Chen, 1995): These indices are integrated across the (a) chlorophyll red edge: 626-795 nm, (b) Red-edge more appropriately 690-740 nm……and other wavelengths.

\[
\lambda_n \left( \rho'(\lambda_i) - \rho'(\lambda_j) \right)
\]

\[
\text{DGVII} = \sum_{\lambda_1}^{\lambda_n} \frac{\lambda_1 \Delta \lambda_1}{\Delta \lambda_1}
\]

Where, I and j are band numbers, \(\lambda\) = center of wavelength, \(\lambda_1 = 0.626 \, \mu m\), \(\lambda_n = 0.795 \, \mu m\), \(\rho'\) = first derivative reflectance.

**Note:** HDGVIs are near-continuous narrow-band spectra integrated over certain wavelengths.
Methods of Modeling Vegetation Characteristics using Hyperspectral Indices
Hyperspectral Derivative Greenness Vegetation Indices (DGVIs) vs. Forest Biomass

DGVI vs. Dry Biomass of Fallows

y = 0.0713e^{9.5734x}

R^2 = 0.8331
Hyperspectral Data (Imaging Spectroscopy data)

HVls: Biophysical, Biochemical, Pigment, Water, Lignin and cellulose, and Physiology

<table>
<thead>
<tr>
<th>Index</th>
<th>Equation</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>NDVI</td>
<td>(\frac{R_{550}-R_{685}}{R_{550}+R_{685}})</td>
<td>Rouse et al. [15]</td>
</tr>
<tr>
<td>SR</td>
<td>(R_{550}-R_{685})</td>
<td>Jordan [3]</td>
</tr>
<tr>
<td>EVI</td>
<td>(2.5 \frac{R_{550}-R_{685}}{\sqrt{R_{550}+6R_{685}+7.5R_{685}+1}})</td>
<td>Huete et al. [23]</td>
</tr>
<tr>
<td>NDWI</td>
<td>(\frac{R_{670}-R_{685}}{R_{670}+R_{685}})</td>
<td>Gao [29]</td>
</tr>
<tr>
<td>WBI</td>
<td>(R_{670}/R_{685})</td>
<td>Pothuizen et al. [28]</td>
</tr>
<tr>
<td>ARVI</td>
<td>(\frac{R_{550}-R_{560}}{\sqrt{R_{550}+R_{560}+1}})</td>
<td>Kaufman &amp; Tanré [22]</td>
</tr>
<tr>
<td>SAVI</td>
<td>(\frac{(R_{670}-R_{685})}{(R_{670}+R_{685}+1.5)})</td>
<td>Huete [21]</td>
</tr>
<tr>
<td>IDL/IDGVI</td>
<td>(\sum_{\lambda_{c} \rightarrow 685}(R_{\lambda_{c}}-R_{685})/\Delta \lambda_{c})</td>
<td>Elvidge &amp; Chen [1]</td>
</tr>
<tr>
<td>IDZ/IDGVI</td>
<td>(\sum_{\lambda_{c} \rightarrow 685}(R_{\lambda_{c}}-R_{685})/\Delta \lambda_{c})</td>
<td>Elvidge &amp; Chen [1]</td>
</tr>
<tr>
<td>VARI</td>
<td>(R_{670}-R_{550}/(R_{670}+R_{550}))</td>
<td>Gitelson et al. [13]</td>
</tr>
<tr>
<td>VIgreen</td>
<td>(R_{670}-R_{550}/(R_{670}+R_{550}))</td>
<td>Gitelson et al. [13]</td>
</tr>
</tbody>
</table>

**Biochemical**

<table>
<thead>
<tr>
<th>Pigments</th>
<th>Equation</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>SIPI</strong></td>
<td>(R_{670}-R_{650})</td>
<td>Pothuizen et al. [31]</td>
</tr>
<tr>
<td><strong>PSII</strong></td>
<td>(\frac{R_{670}-R_{650}}{R_{670}+R_{650}})</td>
<td>Blackburn [30]</td>
</tr>
<tr>
<td><strong>PSND</strong></td>
<td>(\frac{R_{670}-R_{650}}{R_{670}+R_{650}})</td>
<td>Blackburn [32]</td>
</tr>
<tr>
<td><strong>PSRI</strong></td>
<td>(\frac{R_{670}-R_{660}}{R_{670}+R_{660}})</td>
<td>Merard et al. [33]</td>
</tr>
</tbody>
</table>

**Chlorophyll**

| **CARI** | \(R_{670}-R_{650}+0.2(R_{670}-R_{650})\) | Kim [34] |
| **MCARI** | \(R_{670}+0.2(R_{670}-R_{650})\) | Daughtry et al. [35] |
| **ClChl** | \(R_{670}/R_{660}\) | Gitelson et al. [36] |

**Anthocyanins**

| **ARI**  | \(1/(R_{670}-R_{650})\) | Gitelson et al. [40] |
| **mARI** | \(1/(R_{670}+R_{650})\) | Gitelson et al. [26] |
| **RGR**  | \(R_{670}/R_{650}\) | Gamon & Surfbis [7] |
| **ACI**  | \(R_{670}/R_{650}\) | Van den Berg & Perkins [41] |

**Carotenoids**

| **CHR1** | \(1/(R_{670}+R_{650})\) | Gitelson et al. [42] |
| **CHR2** | \(1/(R_{670}+R_{650})\) | Gitelson et al. [42] |

**Water**

| **NDWI** | \(\frac{R_{380}-R_{685}}{R_{685}+R_{685}}\) | Hunt & Rock [12] |
| **WHI**  | See Above | See Above |
| **MSI**  | \(R_{685}/R_{550}\) | Rock et al. [43] |

**Lignin & Cellulose/Residues**

| **CAI** | \(0.09(0.5R_{380}+R_{820})+R_{210}\) | Daughtry [47] |
| **NDLI** | \(\log(1+R_{380})+\log(1+R_{820})+\log(1+R_{210})\) | Serrano et al. [48] |

**Nitrogen**

| **DDNII** | \(\log(1+R_{380})+\log(1+R_{820})+\log(1+R_{210})\) | Serrano et al. [48] |

**Physiology**

**Light Use Efficiency**

| **RGR, SIPI** | See Above | See Above |
| **PRI**       | \(R_{670}-R_{650}\) | Gamon et al. [9] |

**Stress**

| **MSI**   | See Above | See Above |
| **H2**    | \(\text{H}2\text{O first derivative (680-750 nm)}\) | Hauer et al. [10] |
| **RSVI**  | \(R_{685}-R_{670}\) | Merion & Huntsing [52] |

Note: see chapter 14, Roberts et al.
## Hyperspectral Data (Imaging Spectroscopy data)

HVIs: Biophysical, Biochemical, Pigment, Water, Lignin and cellulose, and Physiology

<table>
<thead>
<tr>
<th>Spectral index</th>
<th>Characteristics &amp; functions</th>
<th>Definition</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Multiple bioparameters:</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>LI, Lepidium Index</td>
<td>To be sensitive to the uniformly bright reflectance displayed by <em>Lepidium</em> in the visible range.</td>
<td>$R_{550}/R_{586}$</td>
<td>[20]</td>
</tr>
<tr>
<td><strong>NDVI, Normalized Difference Vegetation Index</strong></td>
<td>Respond to change in the amount of green biomass and more efficiently in vegetation with low to moderate density.</td>
<td>$(R_{NIR}-R_N)/(R_{NIR}+R_N)$</td>
<td>[74]</td>
</tr>
<tr>
<td><strong>PSND, Pigment-Specific Normalized Difference</strong></td>
<td>Estimate LAI and carotenoids (Cars) at leaf or canopy level</td>
<td>$(R_{660}-R_{470})/(R_{660}+R_{470})$</td>
<td>[74]</td>
</tr>
<tr>
<td><strong>SR, Simple Ratio</strong></td>
<td>Same as NDVI</td>
<td>$R_{NIR}/R_N$</td>
<td>[76,77]</td>
</tr>
<tr>
<td><strong>Pigments:</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Chl\textsubscript{green}, Chlorophyll Index Using Green Reflectance</strong></td>
<td>Estimate chlorophylls (Chls) content in anthocyanin-free leaves if NIR is set</td>
<td>$(R_{660-800}/R_{440-560})-1$</td>
<td>[78]</td>
</tr>
<tr>
<td><strong>Chl\textsubscript{red-edge}, Chlorophyll Index Using Red Edge Reflectance</strong></td>
<td>Estimate Chls content in anthocyanin-free leaves if NIR is set</td>
<td>$(R_{760-800}/R_{690-720})-1$</td>
<td>[78]</td>
</tr>
<tr>
<td><strong>LCI, Leaf Chlorophyll Index</strong></td>
<td>Estimate Chl content in higher plants, sensitive to variation in reflectance caused by Chl absorption</td>
<td>$(R_{680}/R_{710})/(R_{680}+R_{680})$</td>
<td>[79]</td>
</tr>
<tr>
<td><strong>mND\textsubscript{680}, Modified Normalized Difference</strong></td>
<td>Quantify Chl content and sensitive to low content at leaf level.</td>
<td>$(R_{680}/R_{680})/(R_{680}+R_{680})$</td>
<td>[80]</td>
</tr>
<tr>
<td><strong>mND\textsubscript{705}, Modified Normalized Difference</strong></td>
<td>Quantify Chl content and sensitive to low content at leaf level. mND\textsubscript{705} performance better than mND\textsubscript{680}</td>
<td>$(R_{750}/R_{705})/(R_{750}+R_{705})-2R_{445}$</td>
<td>[80,81]</td>
</tr>
<tr>
<td><strong>mSR\textsubscript{705}, Modified Simple Ratio</strong></td>
<td>Quantify Chl content and sensitive to low content at leaf level.</td>
<td>$(R_{750}/R_{445})/(R_{705}/R_{445})$</td>
<td>[80]</td>
</tr>
</tbody>
</table>

**Note:** see chapter 19, Pu et al.
## Hyperspectral Data (Imaging Spectroscopy data)

### HVIs: Biophysical, Biochemical, Pigment, Water, Lignin and cellulose, and Physiology

<table>
<thead>
<tr>
<th>Index</th>
<th>Description</th>
<th>Formula</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>mSR705</td>
<td>Modified Simple Ratio</td>
<td>Quantify Chl content and sensitive to low content at leaf level.</td>
<td>(\frac{R_{750} - R_{445}}{R_{705} - R_{445}})</td>
</tr>
<tr>
<td>NPCI</td>
<td>Normalized Pigment Chlorophyll ratio Index</td>
<td>Assess Cars/Chl ratio at leaf level</td>
<td>(\frac{R_{680} - R_{430}}{R_{680} + R_{430}})</td>
</tr>
<tr>
<td>PBI</td>
<td>Plant Biochemical Index</td>
<td>Retrieve leaf total Chl and nitrogen concentrations from satellite hyperspectral data</td>
<td>(\frac{R_{610}}{R_{550}})</td>
</tr>
<tr>
<td>PRI</td>
<td>Photochemical / Physiological Reflectance Index</td>
<td>Estimate Car pigment contents in foliage</td>
<td>(\frac{R_{631} - R_{670}}{R_{631} + R_{670}})</td>
</tr>
<tr>
<td>PII</td>
<td>Pigment index 2</td>
<td>Estimate pigment content in foliage</td>
<td>(\frac{R_{695}}{R_{760}})</td>
</tr>
<tr>
<td>RGR</td>
<td>Red:Green Ratio</td>
<td>Estimate anthocyanin content with a green and a red band</td>
<td>(\frac{R_{683}}{R_{510}})</td>
</tr>
<tr>
<td>SGR</td>
<td>Summed Green Reflectance</td>
<td>Quantify Chl content</td>
<td>Sum of reflectances from 500 to 599 nm</td>
</tr>
<tr>
<td>CAI</td>
<td>Cellulose Absorption Index</td>
<td>Cellulose &amp; lignin absorption features, discriminates plant litter from soils</td>
<td>(0.5(R_{6020} + R_{6220}) - R_{2100})</td>
</tr>
<tr>
<td>NDLI</td>
<td>Normalized Difference Lignin Index</td>
<td>Quantify variation of canopy lignin concentration in native shrub vegetation</td>
<td>(\frac{\log(1/R_{1754}) - \log(1/R_{1680})}{\log(1/R_{1754}) + \log(1/R_{1680})})</td>
</tr>
<tr>
<td>NDWI</td>
<td>ND Water Index</td>
<td>Improving the accuracy in retrieving the vegetation water content at both leaf and canopy levels</td>
<td>(\frac{R_{660} - R_{1240}}{R_{660} + R_{1240}})</td>
</tr>
<tr>
<td>RVIhyp</td>
<td>Hyperspectral Ratio VI</td>
<td>Quantify LAI and water content at canopy level.</td>
<td>(\frac{R_{1088}}{R_{1148}})</td>
</tr>
<tr>
<td>WI</td>
<td>Water Index</td>
<td>Quantify relative water content at leaf level</td>
<td>(\frac{R_{900}}{R_{970}})</td>
</tr>
</tbody>
</table>

**Note:** see chapter 19, Pu et al.
Hyperspectral Remote Sensing of Vegetation

Study of Pigments: chlorophyll

e.g., Reflectance spectra of beech leaves...red-edge (700-740 nm) one of the best.
Hyperspectral Remote Sensing of Vegetation

Study of Pigments: carotenoids/chlorophyll

e.g., Reflectance spectra of chestnut leaves...difference reflectance of (680-500 nm)/750 nm
quantitative measurement of plant senescence

Note: see chapter 6; Gitelson et al.
Methods of Classifying Vegetation Classes or categories
Increased Accuracies over Broadband Data
Methods of Classifying Vegetation Classes or Categories

Using hyperspectral narrowband data

1. Multivariate and Partial Least Square Regression,
2. Discriminant analysis
3. unsupervised classification (e.g., Clustering),
4. supervised approaches

A. Spectral-angle mapping or SAM,
B. Maximum likelihood classification or MLC,
C. Artificial Neural Network or ANN,
D. Support Vector Machines or SVM,

4. Spectral Matching Technique (SMT)

Excellent for full spectral analysis.....but needs good spectral library

.........All these methods have merit; it remains for the user to apply them to the situation of interest.
Methods of Classifying Vegetation Classes or Categories

Discriminant Model or Classification Criterion (DM) to Test

How Well 12 different Vegetation are Discriminated using different Combinations of Broadbands vs. Narrowbands?

(a) IKONOS

\[ y = -2.6316x^2 + 16.316x + 23.684 \]

\[ R^2 = 0.9333 \]

(b) Landsat ETM+

\[ y = -0.313x^2 + 2.6915x + 36.847 \]

\[ R^2 = 0.7857 \]

(c) Advanced Land Imager (ALI)

\[ y = -0.5436x^2 + 7.917x + 21.816 \]

\[ R^2 = 0.9455 \]

(d) Hyperion

\[ y = -0.1411x^2 + 6.2849x + 21.513 \]

\[ R^2 = 0.9596 \]
Concluding Thoughts I

Hyperspectral (imaging Spectroscopy)

Knowledge Gain in Study of Vegetation
Hyperspectral Remote Sensing of Vegetation
Knowledge Gain and Knowledge Gap After 40 years of Research

1. Hyperspectral narrowbands when compared with broadbands data can significantly improve in:
   1.1. Discriminating\Separating vegetation and crop types and their species;
   1.2. Explaining greater variability in modeling vegetation and crop biophysical, yield, and biochemical characteristics;
   1.3. Increasing accuracies (reducing errors and uncertainties) in vegetation\land cover classification; and
   1.4. Enabling the study of specific biophysical and biochemical properties from specific targeted portion of the spectrum.

2. About 33 narrowbands, in 400-2500 nm, provide optimal information in vegetation studies. These waveband centers are identified in this study. A nominal 3 to 5 nm wide bandwidth is recommended for all wavebands;

3. Advances in methods and approaches of hyperspectral data analysis in vegetation studies.

U.S. Geological Survey
U.S. Department of Interior
Knowledge Gain in using Hyperspectral Narrowband Data in Study of Vegetation

1.1a. Discriminating\Separating Vegetation Types

Note: Distinct separation of vegetation or crop types or species using distinct narrowbands

Numerous narrow-bands provide unique opportunity to discriminate different crops and vegetation.
Methods of Separating Vegetation Classes or Categories
Hyperion Narrowbands in Separating Vegetation\Crop Types (e.g., Crops in Brazil)

Relationships between red and near infrared (NIR) Hyperion bands for the studied crop types. The triangle is discussed in the text.

Variation in NIR-1/red and SWIR-1/green reflectance ratios for the crop types under study.

Note: see chapter 17

U.S. Geological Survey
U.S. Department of Interior
Knowledge Gain in using Hyperspectral Narrowband Data in Study of Vegetation

1.2a. Improved biophysical and biochemical models of Vegetation

Note: Improved models of vegetation biophysical and biochemical variables: The combination of wavebands in Table 28.1 or HVIs derived from them provide us with significantly improved models of vegetation variables such as biomass, LAI, net primary productivity, leaf nitrogen, chlorophyll, carotenoids, and anthocyanins. For example, stepwise linear regression with a dependent plant variable (e.g., LAI, Biomass, nitrogen) and a combination of “N” independent variables (e.g., chosen by the model from Table 28.1) establishes a combination of wavebands that best model a plant variable.

Narrow-band indices explain about 13 percent greater variability in modeling crop variables.
Knowledge Gain in using Hyperspectral Narrowband Data in Study of Vegetation

1.3a. Improved Classification Accuracies (and reduced errors and uncertainties)

Note: Overall Accuracies and $K_{hat}$ Increase by about 30% using 20 narrow-bands compared to 6 non-thermal TM broad-bands in classifying 12 classes

Overall accuracy (%) = $-0.0224x^2 + 1.5996x + 66.606$

$R^2 = 0.9688$

Khat (%) = $-0.0282x^2 + 2.0093x + 57.617$

$R^2 = 0.9695$

Note: Improved accuracies in vegetation type or species classification: Combination of these wavebands in Table 28.1 help provide significantly improved accuracies (10-30%) in classifying vegetation types or species types compared to broadband data;
Knowledge Gain in using Hyperspectral Narrowband Data in Study of Vegetation

1.3b. Improved Classification Accuracies (and reduced errors and uncertainties)

Stepwise Discriminant Analysis (SDA)- Wilks’ Lambda to Test: How Well Different Forest Vegetation are Discriminated from One Another

Lesser the Wilks’ Lambda greater is the separability. Note that beyond 10-20 wavebands Wilks’ Lambda becomes asymptotic.

- Fallow
  1-3 yr vs. 3-5 yr vs. 5-8 yr
- Primary forest
  Pristine vs. degraded
- Secondary forest
  Young vs. mature vs. mixed
- Primary + secondary forests + fallow areas
  All above

Number of bands

Wilk’s lambda
Knowledge Gain in using Hyperspectral Narrowband Data in Study of Vegetation

1.2b. Improved biophysical and biochemical models of Vegetation

21 bands predicting biomass compared to actual biomass of all rainforest vegetation

\[ y = 0.9697x + 1.8784 \]
\[ R^2 = 0.9697 \]

200
300
400
500
600
700
800
900
1000
Wavelength [nm]

R-squared value
0.80-0.90
0.70-0.80
0.60-0.70
0.50-0.60
0.40-0.50
0.30-0.40
> 0.30

\[ y = 0.1106e^{3.9254\times NDV1910675} \]
\[ R^2 = 0.7398 \]

200
300
400
500
600
700
800
900
1000
Wavelength [nm]

RICE

PASTURE

\[ WBM = 0.1106e^{3.9254\times NDV1910675} \]
\[ R^2 = 0.7398 \]
Concluding Thoughts II
Hyperspectral (imaging Spectroscopy)
Potential Products in Study of Vegetation
Hyperspectral (Imaging Spectroscopy) Products

6. Spectral Signature Data Bank of Vegetation Species (e.g., *P. Africana*)

- Hyperion FCC(RGB): 890 nm, 680 nm, and 550 nm
## Hyperspectral (Imaging Spectroscopy) Products

5a. Specific Targeted Portion of the Spectrum to Study Specific Biophysical and Biochemical Property

<table>
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<tr>
<th>Index</th>
<th>Equation</th>
<th>Reference</th>
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<tbody>
<tr>
<td>*NDV1</td>
<td>( (R_{655} - R_{680})(R_{690} - R_{700}) )</td>
<td>Rouss et al. [15]</td>
</tr>
<tr>
<td>*SR</td>
<td>( \frac{R_{660}}{R_{670}} )</td>
<td>Jeon [3]</td>
</tr>
<tr>
<td>*TVI</td>
<td>( 2.5(R_{670} - R_{690})R_{690} \frac{R_{690}^2}{R_{670}^2 + 2.5R_{690}^2 + 1} )</td>
<td>Huete et al. [23]</td>
</tr>
<tr>
<td>*NDVI</td>
<td>( \frac{(R_{665} - R_{700})}{(R_{665} + R_{700})} )</td>
<td>Gao [29]</td>
</tr>
<tr>
<td>*WBI</td>
<td>( R_{650}/R_{700} )</td>
<td>Petuseln et al. [28]</td>
</tr>
<tr>
<td>*ARVI</td>
<td>( (R_{665} - R_{700})/R_{665} + (R_{665} - R_{700}) )</td>
<td>Kaufman &amp; Tanré [22]</td>
</tr>
<tr>
<td>*SAVI</td>
<td>( \frac{(R_{665} - R_{700}) + (R_{665} - R_{700} - 2)(1 + 1)}{1 + (R_{665} - R_{700})} )</td>
<td>Huete [21]</td>
</tr>
<tr>
<td>**1DI_GGV1</td>
<td>( \sum (\frac{R_{665}}{R_{S_b}}) \sum (\frac{R_{665}}{R_{S_b}}) \sum (\frac{R_{665}}{R_{S_b}}) )</td>
<td>Elvidge &amp; Chen [1]</td>
</tr>
<tr>
<td>**1DZ_GGV1</td>
<td>( \sum (\frac{R_{665}}{R_{S_b}}) \sum (\frac{R_{665}}{R_{S_b}}) \sum (\frac{R_{665}}{R_{S_b}}) )</td>
<td>Elvidge &amp; Chen [1]</td>
</tr>
<tr>
<td>*VARI</td>
<td>( \frac{(R_{665} - R_{700})}{R_{665} + R_{700}} )</td>
<td>Gitelson et al. [12]</td>
</tr>
<tr>
<td>*Vgreen</td>
<td>( \frac{(R_{665} - R_{700})}{(R_{665} + R_{700})} )</td>
<td>Gitelson et al. [12]</td>
</tr>
</tbody>
</table>

### Biochemical Indices

#### Pigments

<table>
<thead>
<tr>
<th>Index</th>
<th>Equation</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>*SPI1</td>
<td>( (R_{620} - R_{630})/R_{630} )</td>
<td>Pethisz et al. [11]</td>
</tr>
<tr>
<td>**PPSR</td>
<td>( (R_{650} - R_{660})/R_{665} )</td>
<td>Blackburn [30]</td>
</tr>
<tr>
<td>**PNSD</td>
<td>( [(R_{665} - R_{670})/R_{670}]/[R_{665} - R_{670}]/[R_{665} - R_{670}] )</td>
<td>Blackburn [32]</td>
</tr>
<tr>
<td>**PSRI</td>
<td>( (R_{655} - R_{670})/R_{670} )</td>
<td>Merzdorf et al. [33]</td>
</tr>
</tbody>
</table>

#### Chlorophylls

<table>
<thead>
<tr>
<th>Index</th>
<th>Equation</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>**CAMI</td>
<td>( [(R_{665} - R_{670}) - 0.85(R_{665} - R_{670})] )</td>
<td>Kim [34]</td>
</tr>
<tr>
<td>**MCAMI</td>
<td>( [(R_{665} - R_{670}) - 0.5(R_{665} - R_{670})] )</td>
<td>Daughtry et al. [35]</td>
</tr>
<tr>
<td>**CLPSI</td>
<td>( R_{655}/R_{665} )</td>
<td>Gitelson et al. [36]</td>
</tr>
</tbody>
</table>

#### Anthocyanins

<table>
<thead>
<tr>
<th>Index</th>
<th>Equation</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>**ARI</td>
<td>( (R_{700} - R_{750})/R_{700} )</td>
<td>Gitelson et al. [40]</td>
</tr>
<tr>
<td>**kAR1</td>
<td>( (R_{700} - R_{750})/R_{700} )</td>
<td>Gitelson et al. [40]</td>
</tr>
<tr>
<td>**BRG1</td>
<td>( R_{700}/R_{750} )</td>
<td>Gamon &amp; Sums [7]</td>
</tr>
<tr>
<td>**ACI</td>
<td>( R_{700}/R_{750} )</td>
<td>van den Berg &amp; Perkins [41]</td>
</tr>
</tbody>
</table>

#### Carotenoids

<table>
<thead>
<tr>
<th>Index</th>
<th>Equation</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>**CRI1</td>
<td>( (R_{530} - R_{560})/R_{580} )</td>
<td>Gitelson et al. [42]</td>
</tr>
<tr>
<td>**CRI2</td>
<td>( (R_{530} - R_{560})/R_{580} )</td>
<td>Gitelson et al. [42]</td>
</tr>
</tbody>
</table>

#### Water

<table>
<thead>
<tr>
<th>Index</th>
<th>Equation</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>*NDWI</td>
<td>( (R_{665} - R_{700})/(R_{665} + R_{700}) )</td>
<td>Hunt &amp; Rock [12]</td>
</tr>
<tr>
<td>*NDVI, **WBI</td>
<td>See Above</td>
<td>See Above</td>
</tr>
<tr>
<td>**MSI</td>
<td>( R_{650}/R_{700} )</td>
<td>Rock et al. [41]</td>
</tr>
</tbody>
</table>

#### Lignin & Cellulose/Residues

<table>
<thead>
<tr>
<th>Index</th>
<th>Equation</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>**CAI</td>
<td>( 100 \times 0.5(\log_{10}(R_{2815}) - 2.311) )</td>
<td>Daughtry [42]</td>
</tr>
<tr>
<td>**NDLI</td>
<td>( \log_{10}(R_{2815} + 1) - \log_{10}(R_{2815}) )</td>
<td>Daughtry [47]</td>
</tr>
<tr>
<td>**NDN1</td>
<td>( \log_{10}(R_{2815} + 1) - \log_{10}(R_{2815}) )</td>
<td>Senso et al. [48]</td>
</tr>
</tbody>
</table>

#### Nitrogen

<table>
<thead>
<tr>
<th>Index</th>
<th>Equation</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>**NNDN</td>
<td>( \log_{10}(R_{2815} + 1) - \log_{10}(R_{2815}) )</td>
<td>Senso et al. [48]</td>
</tr>
</tbody>
</table>

#### Physiology

<table>
<thead>
<tr>
<th>Index</th>
<th>Equation</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>**RRI1, **SPI1</td>
<td>See Above</td>
<td>See Above</td>
</tr>
<tr>
<td>**PRI1</td>
<td>( R_{665}/R_{700} )</td>
<td>Gamon et al. [9]</td>
</tr>
<tr>
<td>**PRI2</td>
<td>( R_{665}/R_{700} )</td>
<td>Gamon et al. [9]</td>
</tr>
<tr>
<td>**MSI</td>
<td>See Above</td>
<td>See Above</td>
</tr>
<tr>
<td>**REP</td>
<td>( \max(\text{first derivative}, 600-750 \text{ nm}) )</td>
<td>Horler et al. [10]</td>
</tr>
<tr>
<td>**RVVI</td>
<td>( (R_{665} - R_{700})/R_{700} )</td>
<td>Merton &amp; Huntington [32]</td>
</tr>
</tbody>
</table>
Hyperspectral (Imaging Spectroscopy) Products
2. Generating Broadbands (e.g., Landsat, IKONOS) from Narrowbands (e.g., HyspIRI)

**Imaging spectroscopy**: 242 hyperspectral bands, each of 5 or 10 nm wide, in 400-2500 nm spectral range.

**Generated Landsat ETM+ for data continuity**: 6 non-thermal broadbands at 30 m of Landsat ETM+ Generated from a Hyperspectral Sensor

**Generated IKONOS 4 m data**: 4 broadbands at 4 m of IKONOS Generated from a Hyperspectral Sensor
It is also important to know what specific wavebands are most suitable to study particular biophysical and/or biochemical properties. As examples, plant moisture sensitivity is best studied using a narrowband (5 nm wide or less) centered at 970 nm, while plant stress assessments are best made using a red-edge band centered at 720 nm (or an first order derivative index derived by integrating spectra over 700-740 nm range), and biophysical variables are best retrieved using a red band centered at 687 nm. These bands are, often, used along with a reference band to produce an effective index such as a two-band normalized difference vegetation index involving a near infrared (NIR) reference band centered at 890 nm and a red band centered at 687 nm.
Knowledge Gain in using Hyperspectral Narrowband Data in Study of Vegetation

### 2.1a. Thirty-three (33) Optimal Bands in Study of Vegetation

<table>
<thead>
<tr>
<th>A. Blue bands</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>405 Nitrogen, Senescing</td>
</tr>
<tr>
<td>2</td>
<td>450 Chlorophyll, carotenoids, senescing</td>
</tr>
<tr>
<td>3</td>
<td>490 Carotenoid, Light use efficiency (LUE), Stress in vegetation</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>B. Green bands</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>4</td>
<td>515 Pigments (Carotenoid, Chlorophyll, anthocyanins), Nitrogen, Vigor</td>
</tr>
<tr>
<td>5</td>
<td>531 Light use efficiency (LUE), Xanophyll cycle, Stress in vegetation, pest and disease</td>
</tr>
<tr>
<td>6</td>
<td>550 Anthocyanins, Chlorophyll, LAI, Nitrogen, light use efficiency</td>
</tr>
<tr>
<td>7</td>
<td>570 Pigments (Anthrocyanins, Chlorophyll), Nitrogen</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>C. Red bands</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>8</td>
<td>650 Pigment, nitrogen</td>
</tr>
<tr>
<td>9</td>
<td>687 Biophysical quantities, chlorophyll, solar induced chlorophyll Floroscense</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>D. Red-edge bands</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>705 Stress in vegetation detected in red-edge, stress, drought</td>
</tr>
<tr>
<td>11</td>
<td>720 Stress in vegetation detected in red-edge, stress, drought</td>
</tr>
<tr>
<td>12</td>
<td>700-740 Chlorophyll, senescing, stress, drought</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>E. Near infrared (NIR) bands</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>13</td>
<td>760 Biomass, LAI, Solar-induced passive emissions</td>
</tr>
<tr>
<td>14</td>
<td>855 Biophysical/biochemical quantities, Heavy metal stress</td>
</tr>
<tr>
<td>15</td>
<td>970 Water absorption band</td>
</tr>
<tr>
<td>16</td>
<td>1045 Biophysical and biochemical quantities</td>
</tr>
</tbody>
</table>

**Note 1:** Overcomes data redundancy and yet retains optimal solution.

**Note 2:** for each band, a bandwidth of 3 nm will be ideal, 5 nm maximum to capture the best characteristics of vegetation.

---

* = wavebands were selected based on research and discussions in the chapters.

** = when there were close wavebands (e.g., 960 nm, 970 nm), only one waveband (e.g., 970 nm) was selected based on overwhelming evidence as reported in various chapters. This would avoid redundancy.

*** = a nominal 5 nm waveband width can be considered optimal for obtaining best results with above wavebands as band centers. So, for 970 nm waveband center, we can have a band of range of 968-972 nm.

**** = The above wavebands can be considered as optimal for studying vegetation. Adding more waveband will only add to redundancy. Vegetation indices can be computed using above wavebands.

****** = 33 wavebands lead to a matrix of 33 x 33 = 1089 two band vegetation indices (TBVIs). Given that the indices above the diagonal and below diagonal replicate and indices along diagonal are redundant, there are 5.
## Knowledge Gain in using Hyperspectral Narrowband Data in Study of Vegetation

### 2.1b. Thirty-three (336) Optimal Bands in Study of Vegetation

#### E. Far near infrared (FNIR) bands

<table>
<thead>
<tr>
<th>Band No.</th>
<th>Wavenumber (nm)</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>17</td>
<td>1100</td>
<td>Biophysical quantities</td>
</tr>
<tr>
<td>18</td>
<td>1180</td>
<td>Water absorption band</td>
</tr>
<tr>
<td>19</td>
<td>1245</td>
<td>Water sensitivity</td>
</tr>
</tbody>
</table>

#### F. Early short-wave infrared (ESWIR) bands

<table>
<thead>
<tr>
<th>Band No.</th>
<th>Wavenumber (nm)</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>20</td>
<td>1450</td>
<td>Water absorption band</td>
</tr>
<tr>
<td>21</td>
<td>1548</td>
<td>Lignin, cellulose</td>
</tr>
<tr>
<td>22</td>
<td>1620</td>
<td>Lignin, cellulose</td>
</tr>
<tr>
<td>23</td>
<td>1650</td>
<td>Heavy metal stress, Moisture sensitivity</td>
</tr>
<tr>
<td>24</td>
<td>1690</td>
<td>Lignin, cellulose, sugar, starch, protein</td>
</tr>
<tr>
<td>25</td>
<td>1760</td>
<td>Water absorption band, senescence, lignin, cellulose</td>
</tr>
</tbody>
</table>

#### G. Far short-wave infrared (FSWIR) bands

<table>
<thead>
<tr>
<th>Band No.</th>
<th>Wavenumber (nm)</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>26</td>
<td>1950</td>
<td>Water absorption band</td>
</tr>
<tr>
<td>27</td>
<td>2025</td>
<td>Litter (plant litter), lignin, cellulose</td>
</tr>
<tr>
<td>28</td>
<td>2050</td>
<td>Water absorption band</td>
</tr>
<tr>
<td>29</td>
<td>2133</td>
<td>Litter (plant litter), lignin, cellulose</td>
</tr>
<tr>
<td>30</td>
<td>2145</td>
<td>Water absorption band</td>
</tr>
<tr>
<td>31</td>
<td>2173</td>
<td>Water absorption band</td>
</tr>
<tr>
<td>32</td>
<td>2205</td>
<td>Litter, lignin, cellulose, sugar, starch, protein; Heavy metal stress</td>
</tr>
<tr>
<td>33</td>
<td>2295</td>
<td>Stress and soil iron content</td>
</tr>
</tbody>
</table>

**Note 1:** Overcomes data redundancy and yet retains optimal solution.

**Note 2:** for each band, a bandwidth of 3 nm will be ideal, 5 nm maximum to capture the best characteristics of vegetation.

---

* = wavebands were selected based on research and discussions in the chapters;
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***** = 33 wavebands lead to a matrix of 33 x 33 = 1089 two band vegetation indices (TBVIs). Given that the indices above the diagonal and below diagonal replicate and indices along diagonal are redundant, there are 5.
Hyperspectral Data on Tropical Forests
Advances in Combining Hyperspectral and LIDAR over Tropical Forests

**Hyperspectral for**
- canopy
- biochemistry

**LIDAR for**
- canopy structure including height, crown shape, leaf area, biomass, and basal area

**Hyperspectral + LIDAR for**
- characterize parameters such as height, canopy cover, leaf area, canopy chlorophyll content, and canopy water content

Note: see chapter 20, Thomas et al.
Publications

Hyperspectral Remote Sensing of Vegetation
Hyperspectral Remote Sensing of Vegetation

References Pertaining to this Presentation

Hyperspectral Remote Sensing Vegetation

References Pertaining to this Presentation


